CycleGAN Image Translation

Vision And Perception

SAPIENZA
UNIVERSITÀ DI ROMA

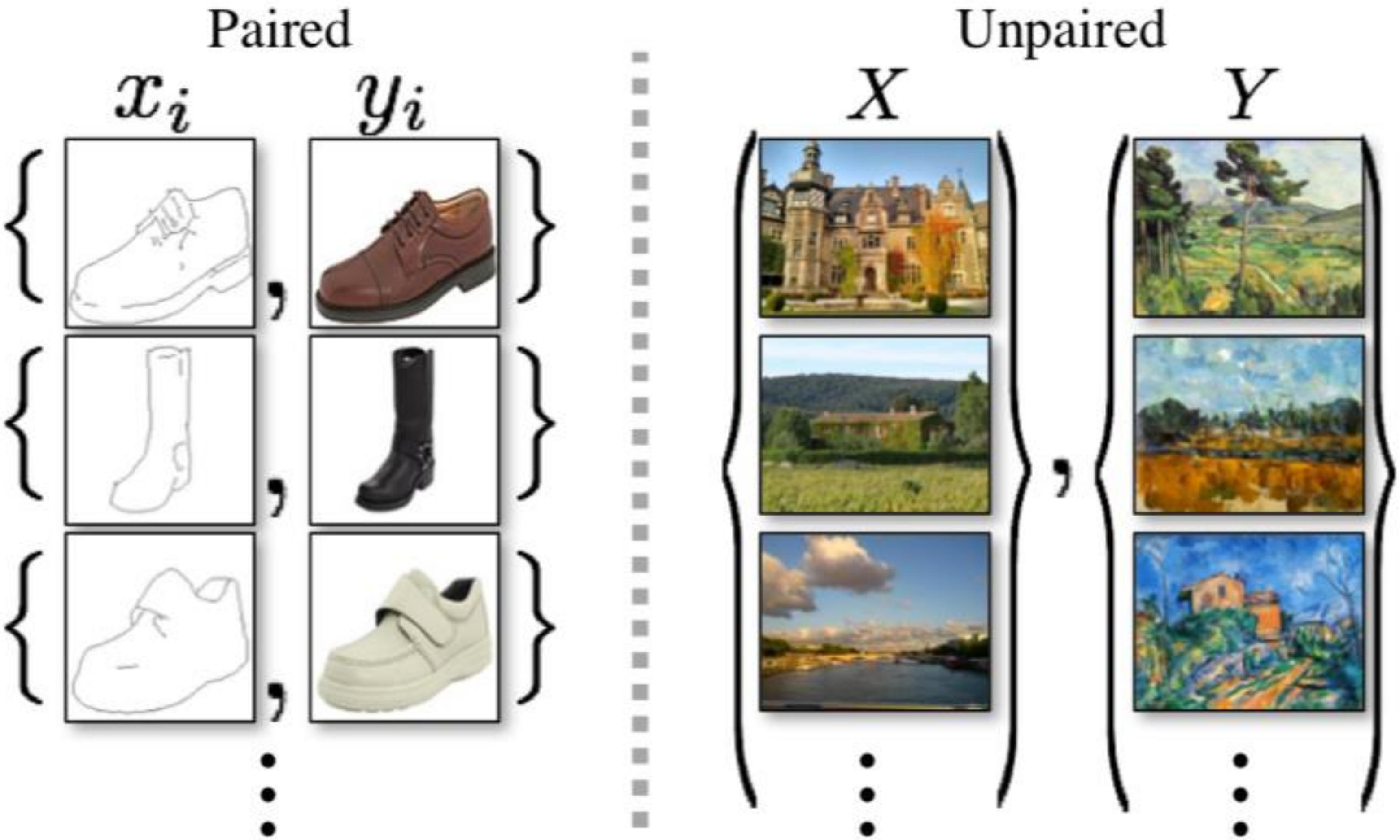
Presented To : Prof. Irene Amerini &
Prof. Paolo Russo

Presented By : Sameer Ahmed

What is CycleGAN?

CycleGAN is a deep learning model that is specifically designed for unpaired image-to-image translation tasks. It aims to learn mappings between two different domains without the need for paired training data, meaning there is no requirement for corresponding images in the two domains during the training process.

- **Unpaired (Means Un-supervised Learning)**
  - Example: CycleGAN
- **Paired (Means Supervised Learning)**
  - Example: Pix2Pix


Paired
x_i
y_i
Unpaired
X
Y

Advantages of CycleGAN over Pix2Pix:

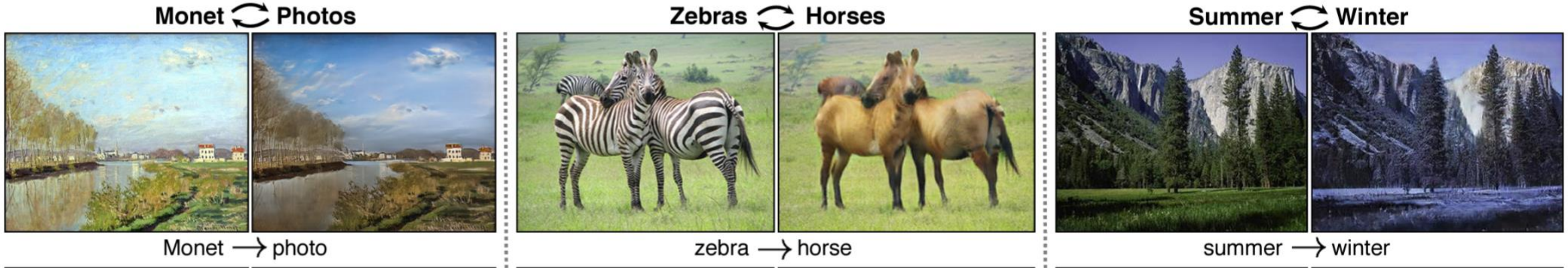
Why we use CycleGAN, If we have Supervised Learning technique Like Pix2Pix?

The reason behind that, we have to use CycleGAN, instead of Pix2Pix, because for many tasks, paired training data will not be available. We present an approach for learning to translate an image from a source domain X to a target domain Y in the absence of paired example.

Mapping G : X ➡ Y

Dataset

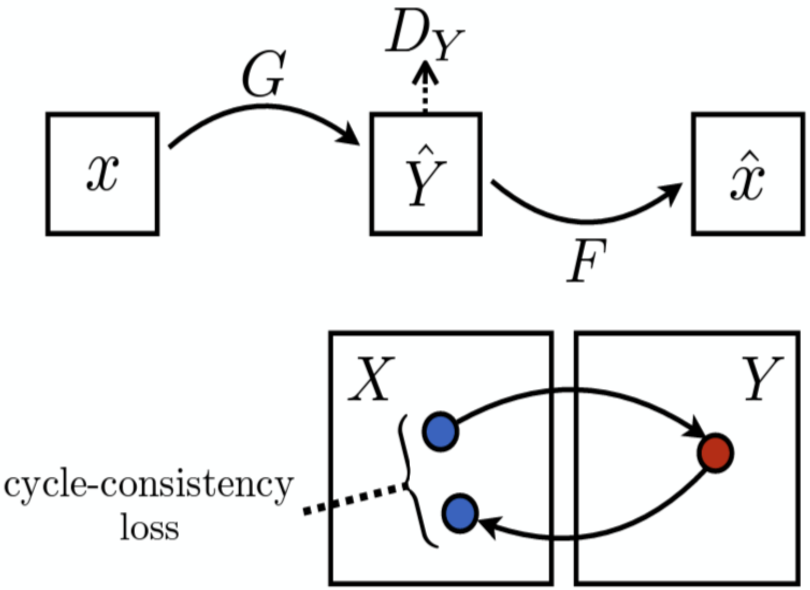
We have different types of dataset for CycleGAN: like Monet and Photos, Horse and Zebra, Summer and Winter, etc. But here I am using **Horse and Zebra dataset**, Although I tried Monet and Photos dataset as well, but due to the limitation of colab GPU, I am not able to achieve some result. So, I only use Horse and Zebra dataset for this project.



Cycle Consistency

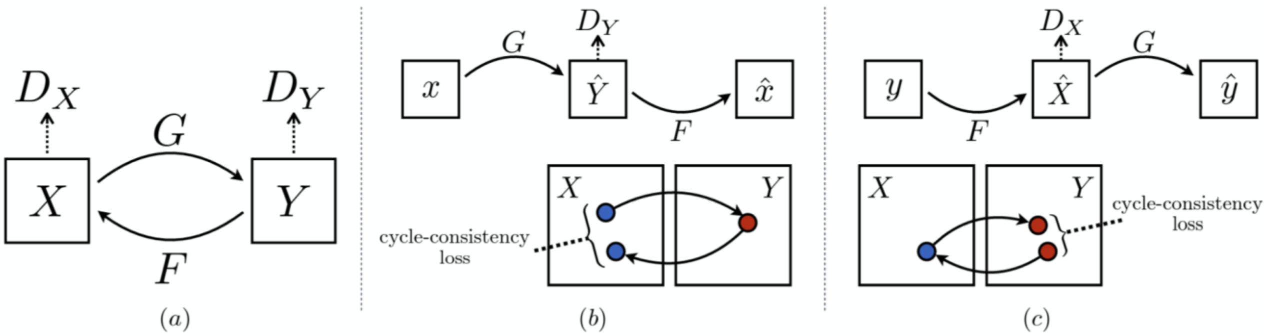
Here, We not use only adversarial loss, but also here we use cycle consistence loss.

Cycle consistence loss is to enforce F(G(X))≈X (and vice versa), Means convert horse to zebra then we can convert again from the zebra to the identical horse.



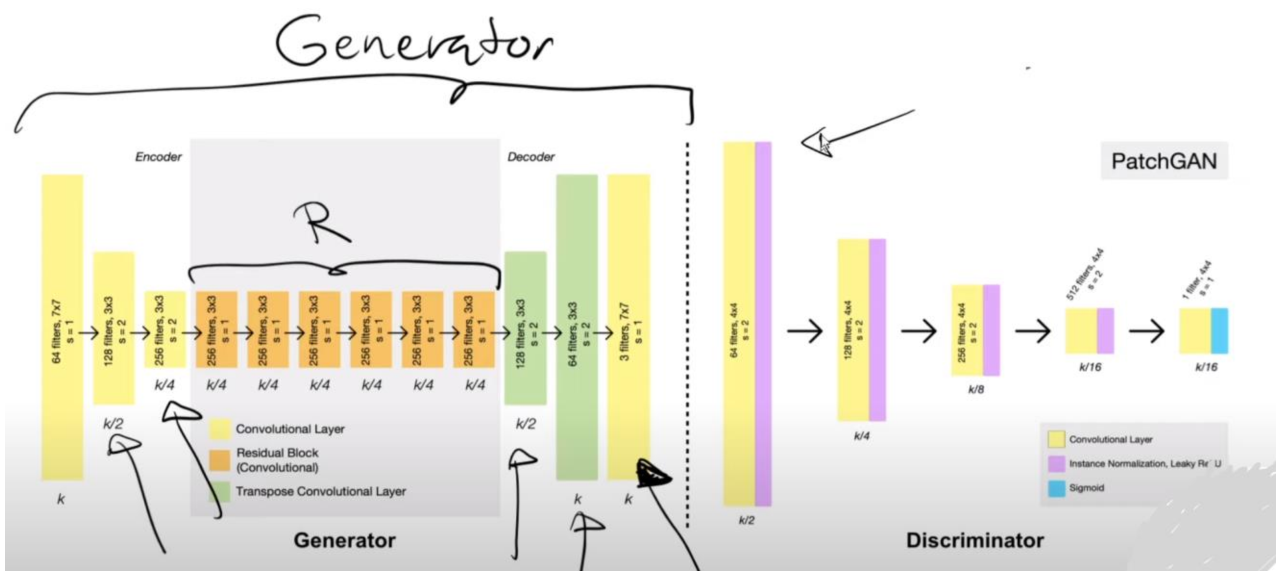
Flow of the model

- X = Horse
- Y = Zebra
- G = Generator for hose to zebra
- F = Generator for zebra to horse
- Dx = Discriminator of horse
- Dy = Discriminator of zebra



Model Architecture

In Generator, we also use U-NET Architecture



Loss Function

In Horse and Zebra Dataset we have 2 losses.

- Adversarial Loss
- Cycle Consistence Loss

Adversarial Loss

The adversarial loss aims to train the generator to produce realistic images by distinguishing them from the real images using Mean Squared Error (MSE) loss.

Cycle Consistency Loss

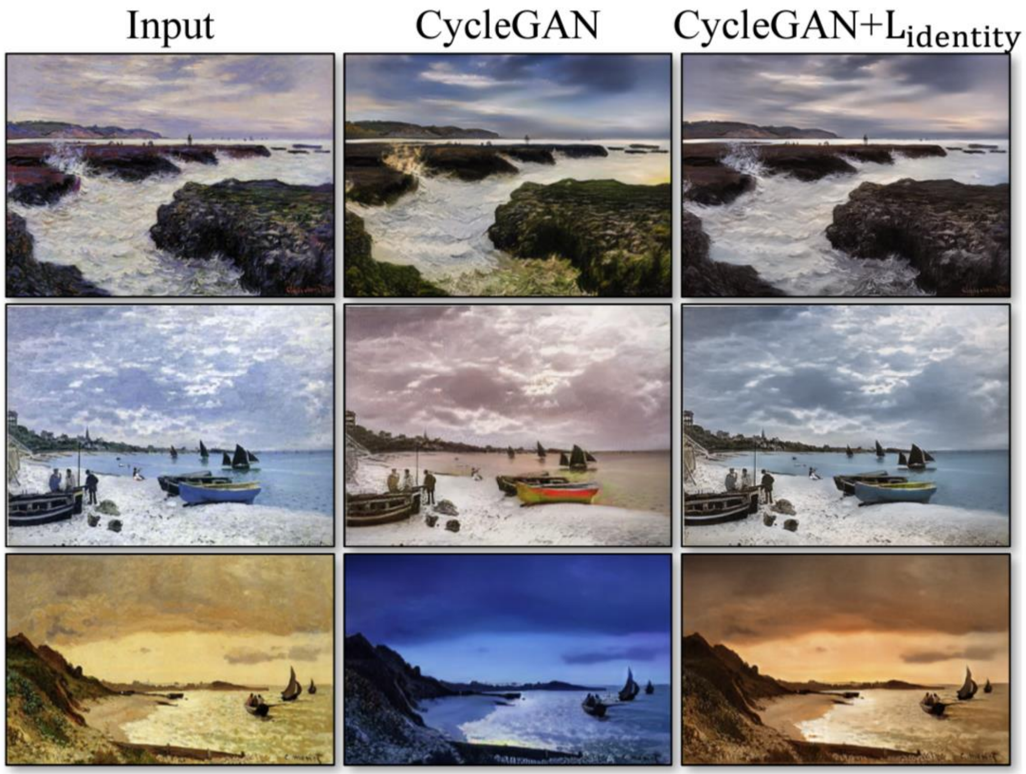
For the cycle consistency loss, the **Wasserstein loss** is employed instead of the traditional L1 norm loss (According to the paper). It ensures that translating an image from one domain to another and then back again generates a reconstructed image that closely resembles the original.

Wasserstein Loss = Mean of f(x)- Mean of f(G(x))
Mean of f(x)- = Mean of Real Samples
Mean of f(G(x)) = Mean of Generated Samples

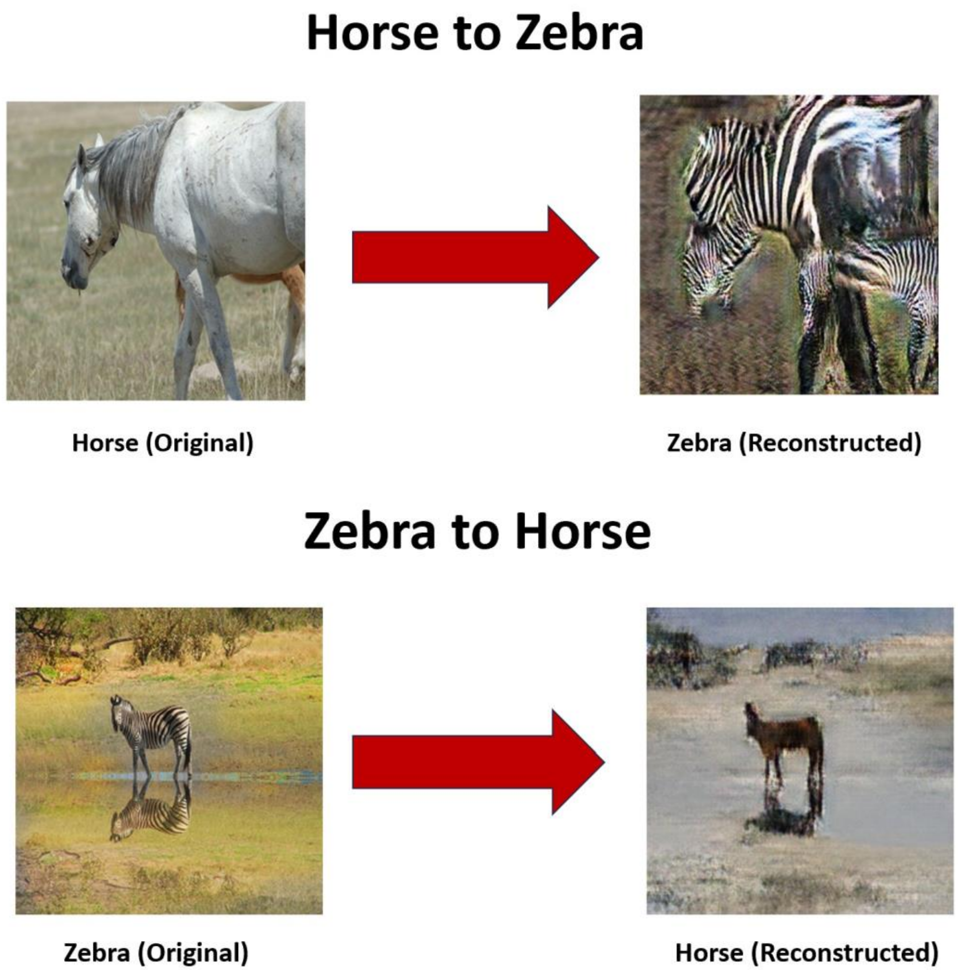
Note: L1 norm loss, Is quite work better instead of Wasserstein loss, the reason behind that because L1 norm loss is give identical results.

Identical Loss (optional)

For panting ➡ photo, we find that it is helpful to introduce an additional loss to encourage the mapping top reserve color composition between the input and output.



Results


Horse to Zebra
Horse (Original)
Zebra (Reconstructed)
Zebra to Horse
Zebra (Original)
Horse (Reconstructed)

Limitation of Our Model

- Due to limitations in the training environment (e.g., computational resources, time constraints, or limitations in the Google Colab platform), the model was trained for a reduced number of epochs, stopping at 128 epochs instead of the originally intended 200 epochs. That's the main reason, the model is not quite good.
- Here I am using batch size 8, instead of 1 batch size (According to the paper).
- If I try U-NET architecture most probably it will work better.
- If I change some sort of hyperparameter, It might be work better also.

Limitation of the paper

- On translation task involve color and texture change, the method often succeeds.
- The CycleGAN is not work well for those tasks that required geometrical changes, like dog ➡ cat transfiguration. The failure might be caused because of CycleGAN generator architecture.

THANK YOU FOR YOUR KIND ATTENTION